THE ROLE OF TECHNOLOGICAL AND INDUSTRIAL HETEROGENEITY IN TECHNOLOGY DIFFUSION: A MARKOVIAN APPROACH

by

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Abstract

Recent empirical studies have established the importance of intra and inter-industry heterogeneity in investment in innovation and other outcomes. This paper examines the role of industry and technology heterogeneity in the diffusion of advanced manufacturing technologies from a simple Markovian approach. Using the Maximum Entropy estimator, I estimate transition probabilities and corresponding half-lives, look for outliers in technology and industry diffusion patterns, and try to find explanations of their unusual behavior in idiosyncratic technology and industry characteristics.

A consistent industry-level pattern that emerged is one that relates consumer demand and production processes. It seems that in industries where hand-made products are a sign of quality to the customer, technology spreads very slowly. On the other hand, in industries where demand for sophisticated, high-precision goods is high or in industries where demand-driven product specifications vary quite rapidly over relatively short periods of time, advanced technologies diffuse much more rapidly.

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INTRODUCTION

Economists have long recognized that technological change is a major determinant of productivity growth and that an important part of the process of technological change is the diffusion stage whereby new product and process innovations are put into use. The diffusion of new technologies, however, seems to have been a slow and incremental process and it has been more so for some industries and technologies than for others.

Recent empirical research using micro-data has also documented a remarkable degree of inter and intra-industry heterogeneity in technology investment and other outcomes (e.g., Foster, Haltiwanger and Krizan 2001, Dunne, Haltiwanger and Troske 1997, Bartlesman and Doms 1997, Davis, Haltiwanger and Schuh 1996). Luque's (forthcoming) results indicate that there is a degree of technology heterogeneity that makes the role of uncertainty and irreversibility in innovation investment more applicable to some technologies than to others. Numerous articles in the business literature have also highlighted the importance of industry effects in firms' decision and ability to adopt advanced manufacturing technologies (Porter 1990, Dosi, Teece, and Chytry 1999). In light of this empirical evidence, it then appears relevant to explore the role of technology and industry heterogeneity in the adoption of new technologies.

In this paper I estimate a measure of a technology's rate of diffusion for 10 manufacturing technologies in 39 3-digit manufacturing industries. That is, I estimate transition probabilities and the half-life (an estimate of the number of years before half of potential adopters in an industry adopt a given technology) of industry/technology combinations.

The data I use, the 1988 and 1993 Survey of Manufacturing Technology (SMT), do not constitute a panel nor do they hold information on how long the individual plant has been using a technology. For this reason, I am unable to employ a hazard rate model. However, I can observe the industry-level aggregate proportion of plants using, planning, or not planning to adopt a technology at two points in time (1988 and 1993), which will allow me to estimate transition probabilities for each technology and industry between two technological states.

The ME estimator is a fairly novel estimator in the economics field and is especially suitable for cases like the present one where the number of states (3) is greater than the number of transitions (1), and where we observe the aggregate proportion of plants in each state, but not each plant in either of the three states over time.

Using the estimated transition probabilities and the corresponding half-lives, I look for outliers in technology and industry diffusion patterns, and try to find explanations of their unusual behavior in idiosyncratic technology and industry characteristics. In several cases I find factors that may help us understand why the diffusion rates seem so unusual.

In line with the recent theoretical innovation investment models that emphasize the role of uncertainty in technology adoption, I develop a simple Markovian search model that accounts for the value of waiting to invest.[1]

The paper is organized as follows. In the next section, I present a simple Markovian search model. In Section III, I briefly describe the data and present the estimation procedure to calculate transition probabilities by industry and technology. In Section IV, I present and discuss the results using the time-dimension of the data. I conclude in Section V.

I. A SIMPLE MARKOVIAN MODEL

The Markov process in discrete time is a probability model that has been widely used by economists as a basis for summarizing and characterizing the information in economic data in terms of transition probabilities. Here I present an outline of a simple Markovian model to motivate the estimation of transition probabilities.

Suppose that a new technology appears in t_0, and that in each time period plants observe a "message" m_t regarding the "status" of the new technology ($t = 0, 1, ..., T$). Assume that these messages are independent and identically distributed random variables. However, plants do not know what the true underlying probability distribution of the "messages" is; in particular, plants know that the probability distribution is either f_0 or f_1, and they are trying to decide which one is the true underlying distribution:

$f_0 \Rightarrow$ new technology is the new technological "status quo"

$f_1 \Rightarrow$ new technology is not the new technological "status quo"

Let p_t be the subjective probability that f_0 is the true underlying distribution, and let p_0 be given by prior beliefs. At time t, after having observed $m_1, m_2, ... m_t$, plants may stop observing and choose either f_0, f_1 or pay a searching cost of 'S' (per period) and observe m_{t+1}.

If a plant stops observing and makes a choice, then it incurs an expected loss that will depend on the choice made. If the choice is correct, the loss is zero. If the choice is incorrect, it will incur a loss, $L > 0$:

i) Expected (marginal) loss if it chooses f_0 (i.e., if it adopts the new technology):

$$(1 - p)(L) + (p)(0)$$

ii) Expected (marginal) loss of choosing f_1 (i.e., never investing in new technology):

$$(p)(L) + (1 - p)(0)$$

Overtime, the plant's beliefs are updated according to Bayes' rule. Then, the posterior subjective probability that f_0 is true given the plant have observed some 'm' at time t is given by:

$$p_{t+1} = \frac{p_t\ f_0(m_t)}{[\,p_t\ f_0(m_t) + (1 - p_t)\, f_1(m_t)]}$$

Finally the goal is to obtain the optimal cost or loss function *V(p)*, which is defined as the minimum of the expected discounted loss of choosing f_0, the expected discounted loss of choosing f_1, and the expected discounted cost of sampling more:

$$V(p) = \min\,[(1 - p)(L) + p(0)\,,\, p(L) + (1 - p)(0)\,,\, S + \beta\, E\,[V(p_{t+1})]]$$

with terminal condition:

$$V(p_T) = \min\,[pL\,, (1 - p)\, L]$$

where β is the discount factor.

In Appendix A, I show that there exist a p^* and a p^{**}, where $p^* < p^{**}$, such that the plant stops and chooses f_0 if $p > p^{**}$, stops and chooses f_1 if $p < p^*$, and continues sampling otherwise (see Figure 1 in Appendix A). Notice that there is a value in waiting to invest in the new technology; that is, the future is uncertain and it pays the plant to wait until more is known about the new technology (see Figure 2 in Appendix A).

II. THE MAXIMUM ENTROPY ESTIMATOR

Data

I employ the 1988 and 1993 Survey of Manufacturing Technology (SMT). In 1988 and 1993, the SMT surveyed approximately 10,000 manufacturing plants in SICs 34-38 about the use of 17 separate technologies (see Appendix A for a description of the technologies). The 3-digit industries under examination are those included in major industry groups 34 - Fabricated Metal Products, 35 -Nonelectrical Machinery, 36 - Electric and Electronic Equipment, 37 - Transportation Equipment, and 38 - Instruments and Related Products.

The drawback of the SMT is that it was not designed to be a panel, nor do they hold information on how long the individual plant has been using a technology.[2] Instead, I observe the aggregate proportion of plants in an industry that are either planning to adopt, using or not planning to adopt a technology in two points in time, 1988 and 1993.

Estimation

In this section, I use the (limited) time-dimension of the data to estimate transition probabilities between the technological states. Some of these (i.e., from planning to adopt to adopting) I then convert into average half-life of adoption. The ME estimator is especially suitable for cases like the present one where the number of states (3) is greater than the number of transitions (1), and where we observe the aggregate proportion of plants in each state, but not each plant in either of the three states over time. The results from this estimation produce transition probabilities by industry and technology that will indicate which industries' and/or technologies' adoption pattern is relatively unusual.

Formally, a Markov process with K states may be written as a system of linear equations. For a collection of plants, the expected proportion of the group occupying state i at period t, y_{it}, may be computed as:

$$y_{it} = \sum_{j=1}^{K} y_{jt-1}\, p_{ji} \qquad \forall\, i = 1, \ldots, K$$

where y_{jt-1} is the proportion of plants across the K states in the previous period, $t-1$. The equation may be expressed in matrix form as $\boldsymbol{y_t} = \boldsymbol{y_{t-1}P}$, where $\boldsymbol{y_{t-1}}$ is the $(1xK)$ vector of proportions falling in the k^{th} Markov state in time $(t-1)$, $\mathbf{y_t}$ represents the $(1xK)$ vector of proportions falling in each of the Markov states in time t, and $\boldsymbol{P}$ is the (KxK) Markov transition probability matrix.

The transition relation may be rewritten as:

$$\begin{bmatrix} y_2 \\ \vdots \\ y_T \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_{T-1} \end{bmatrix} P \quad \text{or} \quad \begin{bmatrix} y_{12} \\ \vdots \\ y_{1T} \\ y_{21} \\ \vdots \\ y_{KT} \end{bmatrix} = (I_K \_ X_T) \begin{bmatrix} p_{11} \\ \vdots \\ p_K 1 \\ p_{12} \\ \vdots \\ p_{KK} \end{bmatrix}$$

or compactly,

$$y_T = (I_K \otimes X_T)\, \boldsymbol{p} \qquad \text{where } X_T = \text{vec (lagged } ys\text{)}$$

which takes the same functional form as the problem of solving a system of linear equations $\boldsymbol{y} = \boldsymbol{Xp}$, where $\boldsymbol{y}$ is a vector of observations of the dependent variable, $\boldsymbol{X}$ is a matrix of observations of independent variables and $\boldsymbol{p}$ is a vector of unknown parameters to be estimated.

To solve this problem using traditional methods, I need to find an inverse matrix $\boldsymbol{A}$ such that $\boldsymbol{p} = \boldsymbol{Ay}$. However, the existence of $\boldsymbol{A}$ depends on the properties of $\boldsymbol{X}$ as follows:

i) If $T = K$ (i.e., the number of observations = the number of unknowns), the problem is said to be just-identified and $\boldsymbol{A} = \boldsymbol{X}^{-1}$,

ii) If $T>K$, the problem is over-identified and $\boldsymbol{A} = \boldsymbol{(X'X)^{-1} X'}$,

iii) If $T<K$, an inverse matrix does not exist; that is, many versions of $\boldsymbol{p}$ may satisfy the observed relation, $\boldsymbol{y} = \boldsymbol{Xp}$ and there is no objective mean for recovering $\boldsymbol{p}$ by traditional methods.

Unfortunately in my case, I cannot use standard methods of estimation such as Maximum Likelihood or GLS to compute the transition probabilities because the number of states (3: planning to use, using, not planning to use) is greater than the number of transitions (1), so the matrix inversion required to recover the transition probabilities is not possible. Instead, I employ the Maximum Entropy estimator which has been proven to perform well in cases such as this (see Lee and Judge, 1993). In order to estimate the Markovian transition probabilities, I need the proportion of plants in a given industry that are in a particular state at several points in time (see Lee, Judge and Zellner (1977)).

The Maximum Entropy estimator allows me to recover ***P*** by maximizing:

$$H(p) = -\sum_{i=1}^{K} \sum_{j=1}^{K} p_{ij} \log(p_{ij})$$

subject to: $\boldsymbol{y_t = y_{t-1}P}$ for t = 2, ..., T (consistency constraint)

$$\sum_{j=1}^{K} p_{ij} = 1 \qquad \forall\, i = 1, ..., K \qquad \text{(additivity constraint)}$$

By maximizing H(p) subject to the additivity constraint and the observed information (consistency constraint), the Maximum Entropy distribution "agrees with what is known, but expresses 'maximum uncertainty' with respect to all other matters" (Jaynes, 1968). In other words, out of all the possible probability distributions that could characterize the data, I choose the one that imposes the least information constraint on the data. The solution is also associated with the frequency distribution that can generate the observed information in the largest number of ways.[3]

Once I have estimated the transition probabilities, I use them to obtain the average half life of adoption. To do this, assume a constant hazard of adoption that takes the following form[4]: $\lambda = \frac{p}{n}$

where λ is the estimated half-life, *p* is the transition probability from not using to using the technology, and *n* is the number of years over which the transition is measured (in this case 5).

Then I solve the following for *t*, the half-life of the industry/technology combination: $0.5 = F(t;\lambda)$ *where* $F(.)$ *is the cumulative exponential* $= 1 - \exp(-\lambda * t)$.

This implies that the half-life for a constant hazard function is:

$$t = \ln\frac{2}{\lambda}.$$

IV. RESULTS

I begin the analysis by estimating transition probabilities for four sets of changes. They are: ‘planning to adopt’ to ‘adopting’, ‘planning to adopt’ to ‘planning to adopt’, ‘planning to adopt’ to ‘not planning to adopt’, and from ‘not planning to adopt’ to ‘adopting’. I perform the estimation for two groups of five technologies. They are:

1) The Fabrication/Machining and Assembly Group: CNCs, FMS, Lasers, Robotics (Pick-up and Place), Robotics (Other).
2) The Communication and Control Group: Programmable Controllers, Local Area Network (LAN) for factory use, LAN for Technical Data, Computers for Control on the Factory Floor, and Intercompany computer network.

The results are shown in panels 1 through 10 in Appendix C. In each of the panels there are four graphs showing the transition probabilities on the vertical axis and the industry on the horizontal. Each graph depicts a unique transition between one of the following sets of states: Planing to Use to Using, Planing to Use to Planning to Use, Planning to Use to Not Planning to Use, and Not Planning to Use to Using. Although I will analyze these transition probabilities, I am most interested in computing average industry half-lives (an estimate of the number of years before half of potential adopters in an industry adopt a given technology) based on the Planning to Use to Using transition probabilities. For both sets of statistics, I focus my analysis on two dimensions. First, I search for signs of cross-technology differences that are consistent across industry type. Second, I look for cross-industry differences in behavior that are consistent across technology.

1. *Cross-Industry Differences*

Consider the adoption half-lives shown in Table 1. Each column is for a particular technology. The rows are for three digit industries. For example, the first entry in the first row shows that the half-life of CNC technologies in SIC 341 (Metal Cans and Shipping Containers) is 11 years. That is, in approximately 11 years from the time of the survey (1993), one-half of the plants in SIC 341 can be expected to be using this technology if I assume a constant diffusion rate.

1.a. Industries With Rapid Technology Diffusion Rates:

A few industries's half-lives appear to be consistently shorter than the other sectors' for almost any technology. Examples of this are SICs 351 (Engines and Turbines) and 381 (Search, Detection, Navigation, Guidance, Aeronautical, and Nautical Systems, Instruments, and Equipment). These sectors' half-lives of adoption are consistently among the lowest for almost any technology, and thus, have the lowest average half-life, implying that the plants in these industries are adopting advanced technologies rapidly, more rapidly than those in other sectors. SIC 351 has the lowest half-life of any industry for 4 of the 10 technologies: CNC, FMS, Technical Data Network (LAN Tech), and Computers Used for Control on the Factory Floor. SIC 381 is lowest for five different technologies: Lasers, Technical Data Network, Factory Network (LAN Factory), Programmable Controller, and Computers Used for Control on the Factory Floor. Neither of these industries has an outstandingly high half-life for any technology, and even when they are not the shortest, they have among the shortest half-life of any industry.

There is something intuitively pleasing about these results. SIC 381 is a distinctive industry within the manufacturing sector. It is composed of unusually large establishments that spend more than average amounts of money on research and development. Plants in this industry had an average of over 330 employees in 1992, compared with 46 for manufacturing overall. Furthermore, according to NSF (1993) while SIC 38 accounted for less than 7% of manufacturing employment, it spent almost 11% of the private R&D funds for manufacturing firms. Also, this industry's products are relatively sophisticated. Its goods include: Aircraft Flight Instruments, Automatic Pilots, Fathometers, Gyrocompases, Inertial Navigation Systems, Navigational Instruments, Radar Systems and Equipment, and Sonar Systems, and Space Vehicle Guidance Systems. It seems proper that industries such as these that are dominated by large plants performing substantial amounts of R&D and producing sophisticated goods should be using advanced technologies more commonly than other industries.

As a typical example, consider Northstar Corporation, one of the leading manufacturers of nautical navigation aides. Northstar is a major manufacturer of Loran and Global Positioning System (GPS) Equipment, two of the major products of this industry. It created the world's first microprocessor-based Loran navigational aide for commercial fishermen. This product was developed by a group of engineers working at a civilian air terminal in an air force base in Massachusetts and the engineers later formed the Northstar Corporation. They later produced several more generations of improved Loran devices. In the last few years however, GPS has become the state-of-the-art navigational aide and most companies in this sector, Northstar included, have kept up with the advance in technology. GPS is a navigation system developed by the Department of Defense (DOD). GPS receivers determines what satellites are visible, where in the sky they're located, and then loads satellite-position data from each one to determine its location.[5]

Northstar is, in turn, a subsidiary of the Canadian Marconi Company (CMC). CMC designs, manufactures, sells, and supports high-technology electronic products for aerospace, nautical, and communication markets. It provides radio and navigational devices to customers such as the U.S. Army and the Italian Navy for use in combat and search-and-rescue operations. Obviously, companies such as these are strongly connected to the scientific community through their large staffs of engineers and scientists striving to advance their already sophisticated products to the next generation. This connection could help them both understand and assimilate advanced manufacturing technologies.

According to its annual report, CMC has a research and development budget exceeding $5 million, and R&D spending does not seem to be unusual for firms in his industry. Given that, numerous authors (Dunne (1993), Cohen and Levinthal (1996)) have noted a correlation between R&D spending and technology adoption, this may be another explanation for the short technology diffusion half-lives found in this industry. Furthermore, some of the industry's products bear a strong relationship to some of the advanced manufacturing technologies. One such example is CMC's aircraft navigation and flight-management systems that rely on laser-based inertial equipment. They also make a laser-designator range-finder for the U.S. Army. Given that firms in this industry produce goods like these, it is perhaps not a coincidence that this industry has the shortest half-life for adopting lasers as an advanced manufacturing technology of any of the industries under examination.

While it is tempting to associated high-technology goods with high-technology production methods and vice-versa, care should be exercised not to confuse fairly simple products with simple manufacturing techniques. An excellent example of this is SIC 341 (Metal Cans and Shipping Containers). It is hard to imagine a more straight-forward product than a metal can. Ball makes over 2000 beverage cans a minute using technology developed in its "Packaging Laboratory" and hosts a container-making technology conference every year in places like Mexico City and Napa Valley. The topics at the conferences range from "technology break-outs" to can tooling, eight-color printing, and necking innovations.

This example makes it easier to understand why the half-lives for some technologies such as FMS (Flexible Manufacturing Systems) are shorter in this industry than in a majority of others.[6]

1.b. Industries With Slow Technology Diffusion Rates:

Just as some industries' half-lives of adoption seemed particularly short, others' seem notably long. While SICs 351 and 381 have relatively short half-lives of adoption, SIC 373 (Ship and Boat Building and Repair) stands out for having consistently long half-lives for almost every technology. Again, investigation of the nature and structure of the industry is informative. This three-digit SIC contains two very different four-digit SICs: 3731 (Ship Building and Repair) and 3732 (Boat Building and Repair). In 1992 there were approximately 600 establishments in the ship building industry with an average of approximately 200 employees and new capital expenditures of around 128 million dollars. Ship building is an industry with a small number of very large, capital intensive establishments. Background checking reveals an advertisement strategy that highlights their technical prowess. For example, Bollinger Shipyards' boasts that "Cutting and machining are done as efficiently as possible using Computer Aided Manufacturing (CAM)". Similarly, the Halter Marine Group's site features the following information: "We are also active internationally with co-production and technology transfer programs ...." and "Advanced technology and methods are employed such as computer aided design and manufacturing, modular construction and zone outfitting".

By contrast, the boat building industry is made up of approximately 2,500 small establishments averaging only 18 workers per physical location and spending only 63 million dollars in new capital. That is, there are nearly five times as many establishments in this industry, they are about one tenth the size of ship building plants and the boat building industry spends half as much on new capital equipment as does the shipbuilding industry. Interestingly, instead of highlighting advanced manufacturing technologies, firms in this industry stress that much of the work is done by hand.

In addition to the descriptive evidence just presented about the market structure of the boat building industry, it is worth pointing out that the transition probabilities in Panels 1-10 are not weighted by employment, so all establishments in SIC 373 received equal weight. This means that the boat building industry will dominate the effects of the ship-building industry in this exercise. It is, therefore, not entirely surprising that it has among the lowest transition probabilities of any industry.

2. *Cross-Technology Differences*

Next, I shift the focus of the analysis to the technological dimension and look for temporal patterns across individual technologies. Again, start by considering the half-life statistics in Table 1. Several broad patterns are apparent in Table 1's columns. First, there is substantial heterogeneity of half-lives both across and within technologies. The 'Other Robots' category is an excellent example of the within-technology heterogeneity. The half-lives for this technology range from a high of 347 years in SIC 341 to a low of 11 years in SIC 379 (Guided Missiles and Space Vehicles and Parts). This indicates that the interaction of industry and technology is important. This may be because of information asymmetries, historical reasons, or simply the suitability of the technology to the industry. I will return to this idea in a discussion later in the chapter.

A good example of cross-technology heterogeneity is a comparison of the results for CNCs and Lasers. The half-life for any industry in the adoption of CNCs is less than the comparable half-life for Lasers.

Note that there seems to be a lower bound on the all of the estimated half-lives of approximately 5 years. None of the half-lives fall below this, though most are not too much longer.[7] On the other hand, there is a great deal more variation at the upper end of the half-life distribution. A few technology/industry combinations exceed 300, one or two are above 100, and a good number range between 20 to 100 years. Some of these half-lives are long enough to indicate that, in practical terms, the technology does not seem to be spreading out within the industry. Some of the reasons for the variation across technologies may lie within their histories.

To help focus on cross-technology heterogeneity, I constructed Table 2, which shows the cross-industry average half-life for each technology. As noted from Table 1, there seem to be two groups of technologies in Table 2. The first group, which includes CNCs, FMS, and Programmable Controllers, shows fairly consistent half-lives of 14 years or less. Notably for CNCs and Programmable Controllers, the typical half-life is far shorter (approximately 10 years). Note also that the variance of the means is far lower for the technologies with the smaller means. In fact, the variances for robots and lasers are orders of magnitudes greater than that for CNCs or Programmable Controllers.

CNCs and Programmable Controllers' half-life of 10 years implies that roughly ½ of the plants in these industries can be expected to be using these technologies by the year 2003.[8] Interestingly, while CNC's use is highest (61.8%), in SIC 35 (Industrial Machinery and Equipment), Programmable Controllers is evenly spread-out across SICs. Also notable is that unlike many other technologies, CNCs and Programmable Controllers are most commonly used by plants over 30 years of age. This evidence indicates that these are widely-used technologies with well-known qualities. It may be that these are important determinants of the technologies' diffusion rates.

As noted earlier, the half-lives for these technologies contrast starkly with the estimated half-lives of Lasers, Pick and Place Robots and Other Robots, whose average half-lives range from approximately 17 to 24 years. Note also that the variances of the half-lives are relatively high compared to the other technologies, reflecting the heterogeneity between industries discussed earlier. There are plausible clues in the history and development of these technologies that may explain why their half lives are so large and vary so much across industries.

Lasers are a relatively new technology. The first working laser was not produced in a laboratory until 1960, and the first complete patent for a working laser was not awarded until 1987, (though the applications were received in the late 1950s).[9] Although there are many different kinds of lasers, some of the most commonly used for manufacturing were not introduced until the mid 1980s or even the 1990s. At the time the initial SMT was conducted (1988), Lasers were a relatively young technology.

Lasers can be used to focus enormous amounts of energy on small spaces and can be used to drill, scribe, cut, or weld materials with precision and without mechanical cutting devices that need periodic replacement and maintenance. These are all excellent qualities, but not every industry has great need of them. Recall the discussion of the boat-building industry. It is fairly difficult to see a large number of applications for industrial lasers in that industry. Indeed, this SIC has the one of the longest half-life for lasers. Furthermore, given the previous discussion of the industry, this rate is likely to be entirely dependent on shipbuilding and repair, not boat-building.

Some of the plants' responses from the 1988 SMT questionnaire corroborate these suspicions. For these three technologies, a very high percentage of survey respondents (for lasers, 53.6%) reported that their reason for not planning to use this technology was that they did not consider it applicable to their operations. This technology also had one of the highest reported incidences of being considered 'not cost effective' by plant managers at approximately 16.7%.

Similar arguments can be made for robotic technologies. While they are not as young as lasers, they have had an especially tumultuous history. The first firms offering robotic technologies to industry were established in the l960s but the main growth spurt occurred in the 1980s, primarily because of large-scale investment by the automobile industry. Table 1 reflects this facet of their history. It shows that SIC 371 (Motor Vehicles and Vehicle Equipment), and SIC 379 (Miscellaneous Transportation Equipment) have the lowest half-lives for robots. However, sales of robotic manufacturing technologies plummeted in the late 1980s when the expected cost reductions failed to materialize (New York Times 9/7/94 p. C7). This facet of their history is also reflected in the survey results. Approximately 44.4% of the respondents reported that they considered Pick and Place Robots not applicable to their operations. The rate was 45.4% for Other Robots. Also, nearly 21% of the survey respondents reported that robot technologies were 'not cost effective' (the highest for any of the technologies in the survey). The effects of these disappointments on the robot-producing industry have been severe. By 1987, net new orders of robots in the U.S. had fallen by over 1/3 from their 1984 levels.

3. *Transitions Between Other States*

Finally, I turn to the average transition probabilities between different types of technology adoption states shown in Table 3. For these other types of transitions, presenting the results in half-lives does not make as much sense as it does to express them as transition probabilities. Therefore, instead of half-lives, Table 3 shows mean transition probabilities for each state change and technology. Note that Table 3 contains data on the following three states not included in either Table 1 or Table 2: Planning to Use to Planning to Use, Planning to Use to Not Planning to Use, and Not Planning to Use to Using the same group of technologies.

First, consider the results for the 'transition' between planning to use and planning to use. Technology and industry combinations that show high transition rates of this type would indicate situations where many plants are not progressing with their plans to adopt the technology. However, the results in Table 3 show fairly low and uniform transition probabilities with mean rates around 0.20; thus, there is little cross-technology heterogeneity and no evidence of outliers on either side of the distribution.

V. CONCLUSION

In this paper I used the time variation in the SMT data to estimate how long it takes for half of the potential users in an industry to adopt a particular technology. To do this, I exploited a new and powerful estimation technique, the Maximum Entropy Estimator. This estimator is especially useful when the number of states is greater than the number of transitions.

I then used the half-lives to identify industries with unusual technology diffusion patterns. In particular, I looked at industries that had particularly short half- lives of diffusion for a broad range of technologies. Some industries in this category produced relatively high-technology goods. For example, SIC 381 (Search, Detection, Navigation, Guidance, Aeronautical, and Nautical Systems, Instruments, and Equipment) showed consistently short half-lives for many technologies, some of which this industry produces as finished goods as well. Others, such as SIC 341 (Metal Cans and Containers), produce low-technology goods using high-technology processes.

There are some industries that had notably low rates of technology diffusion as evidenced by long half-lives. One such example is SIC 373 (Ship and Boat Building and Repairing). This industry has the longest half-life for 6 of the 10 technologies under consideration. I believe that part of the reason for the slower diffusion of technology in this industry is that most boat builders seem to consider hand-made products to be of superior quality to machine-made boats.

A consistent industry-level pattern that seem to emerge is one that relates consumer demand and production processes. It seems that in industries (such as boat-building) where hand-made products are a sign of quality to the customer, technology spreads very slowly. On the other hand, in industries where demand for sophisticated, high-precision goods is high (as the space vehicle guidance systems) or in industries where demand-driven product specifications (e.g., size, design, color) vary quite rapidly over relatively short periods of time (as in the case of can or car manufacturing), advanced technologies diffuse much more rapidly.

Next, I considered individual technologies that had particularly short or long half-lives. I found evidence that the technologies' age and reliability were inversely correlated to the rate at which they are being adopted.

Although constrained by the limited time dimension and level of aggregation of the data, I find that differences in technology diffusion rates are strongly influenced by idiosyncratic technological and industrial characteristics. This lends further support to the emerging literature that emphasizes the importance of idiosyncratic factors to a variety of economic outcomes.

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Table 1: Industry Half-Lives in Years by Technology

SIC	CNC	Lasers	FMS	Robots: P&P	Robots Other	LAN Tech	LAN Factory	Inter Comp	Prog Cntrl	Factory Comp	Average
341	11	N/A	10	14	347	12	12	14	9	9	48.7
342	9	13	13	13	17	12	14	14	10	13	12.8
343	10	33	12	16	37	13	15	15	11	14	17.6
344	10	36	18	93	62	12	14	15	11	14	28.5
345	9	71	13	16	347	13	13	14	11	13	52.0
346	9	18	14	19	16	12	15	12	10	13	13.8
347	12	17	11	142	134	15	21	18	9	17	39.6
348	10	13	13	14	16	10	12	17	11	11	12.7
349	10	35	13	15	29	12	13	15	11	12	16.5
351	8	16	11	12	15	8	9	10	10	8	10.7
352	10	14	14	24	14	12	14	16	12	15	14.5
353	9	44	13	19	16	10	14	17	11	13	16.6
354	7	13	13	12	347	11	13	14	10	9	44.9
355	9	51	13	12	15	11	14	16	11	13	16.5
356	10	15	14	22	44	11	14	16	11	12	16.9
357	10	14	15	19	37	7	8	20	10	10	15.0
358	10	32	16	20	23	12	14	16	11	11	16.5
359	9	21	13	53	304	12	13	13	12	12	46.2
361	9	14	13	14	17	9	12	13	9	9	11.9
362	9	21	12	14	24	9	10	13	11	10	13.3
363	10	13	12	11	14	11	11	11	9	9	11.1
364	11	24	14	12	40	11	12	16	10	14	16.4
365	11	14	12	11	15	12	12	15	10	11	12.3
366	11	24	12	15	18	8	10	15	12	9	13.4
367	11	12	12	13	24	9	10	13	11	10	12.5
369	11	22	12	13	25	11	14	13	11	11	14.3
371	10	18	12	13	12	11	12	11	10	11	12.0
372	10	15	14	19	15	8	10	13	10	9	12.3
373	11	85	24	361	88	13	49	18	29	87	76.5
374	11	74	16	103	16	11	12	13	8	11	27.5
375	12	21	14	15	15	13	15	13	12	13	14.3
376	10	18	16	19	19	9	7	11	11	10	13.0
379	11	33	13	122	11	15	15	20	10	16	26.6
381	10	11	13	12	16	8	7	13	10	8	10.8
382	11	13	14	14	347	9	11	15	12	12	45.8
384	11	14	12	14	25	9	11	17	10	11	13.4
385	11	20	13	15	15	13	15	16	11	12	14.1
386	9	12	12	13	11	11	13	16	11	13	12.1
387	11	N/A	17	13	N/A	11	13	13	11	13	12.8

Table 2: Mean and Variance of Industry Half-Lives by Technology

	CNC	Lasers	FMS	Robots: P&P	Robots: Other	LAN Tech	LAN Factory	Inter Comp	Prog Comp	Factory Comp
Mean	10.1	23.9	13.5	35.1	66.3	10.9	13.4	14.5	10.9	13.6
Variance	1.1	338.6	5.4	3769.6	11429.4	3.4	40.0	5.3	9.3	146.6

Table 3: Mean and Variance of Transition Probabilities by Technology

Technology		Planning to Planning	Planning to Not Planning	Not Planning to Using
CNC	Mean	0.22	0.34	0.40
	Variance	0.002	0.001	0.023
Programmable Controllers	Mean	0.19	0.38	0.33
	Variance	0.005	0.003	0.016
FMS	Mean	0.22	0.42	0.10
	Variance	0.002	0.002	0.004
Lasers	Mean	0.24	0.48	0.04
	Variance	0.007	0.010	0.019
Pick &Place Robots	Mean	0.22	0.47	0.10
	Variance	0.005	0.010	0.023
Other Robots	Mean	0.24	0.51	0.03
	Variance	0.005	0.007	0.001
LAN for Technical Data	Mean	0.22	0.37	0.30
	Variance	0.001	0.004	0.021
LAN for Factory Use	Mean	0.24	0.39	0.23
	Variance	0.002	0.004	0.018
Inter Company Computer Network	Mean	0.25	0.42	0.16
	Variance	0.001	0.003	0.009
Computers for Factory Floor Control	Mean	0.22	0.41	0.28
	Variance	0.002	0.004	0.012

Table 4: Transition Probabilities Between 'Not Planning to Adopt' and 'Adopting' By Industry and Technology

SIC	CNC	LASERS	FMS	P&P Robot	Other Robot	LAN Techn	LAN Factory	Inter Comp	Programm Control	Fact Comp
341	0.09	0.00	0.13	0.09	0.01	0.18	0.23	0.15	0.54	0.40
342	0.56	0.06	0.11	0.14	0.02	0.23	0.15	0.19	0.48	0.26
343	0.45	0.01	0.16	0.04	0.01	0.13	0.08	0.10	0.29	0.21
344	0.55	0.01	0.01	0.03	0.01	0.21	0.09	0.08	0.14	0.09
345	0.49	0.00	0.09	0.04	0.01	0.17	0.17	0.21	0.28	0.27
346	0.52	0.01	0.06	0.07	0.05	0.27	0.18	0.30	0.41	0.25
347	0.03	0.01	0.03	0.01	0.00	0.02	0.01	0.01	0.27	0.08
348	0.52	0.02	0.14	0.12	0.03	0.31	0.22	0.05	0.51	0.31
349	0.49	0.01	0.09	0.05	0.01	0.22	0.19	0.14	0.41	0.28
351	0.46	0.03	0.32	0.21	0.10	0.51	0.48	0.42	0.41	0.40
352	0.49	0.02	0.05	0.01	0.08	0.21	0.15	0.08	0.23	0.15
353	0.55	0.01	0.08	0.01	0.02	0.37	0.14	0.08	0.27	0.21
354	0.58	0.02	0.03	0.03	0.01	0.28	0.19	0.17	0.37	0.38
355	0.58	0.01	0.04	0.03	0.01	0.34	0.15	0.07	0.27	0.22
356	0.55	0.02	0.08	0.01	0.01	0.36	0.16	0.11	0.36	0.26
357	0.16	0.01	0.06	0.06	0.01	0.52	0.46	0.15	0.25	0.36
358	0.46	0.01	0.10	0.01	0.01	0.27	0.20	0.14	0.36	0.30
359	0.64	0.01	0.09	0.01	0.01	0.19	0.15	0.11	0.22	0.27
361	0.53	0.04	0.14	0.09	0.02	0.40	0.29	0.24	0.47	0.42
362	0.46	0.01	0.17	0.10	0.01	0.46	0.37	0.22	0.39	0.35
363	0.36	0.03	0.15	0.27	0.12	0.31	0.27	0.33	0.62	0.45
364	0.23	0.01	0.04	0.11	0.01	0.33	0.21	0.10	0.30	0.22
365	0.34	0.03	0.12	0.29	0.07	0.24	0.29	0.13	0.39	0.31
366	0.26	0.01	0.12	0.06	0.01	0.57	0.46	0.15	0.17	0.42
367	0.43	0.10	0.19	0.14	0.01	0.45	0.38	0.22	0.29	0.38
369	0.21	0.01	0.12	0.10	0.01	0.31	0.18	0.24	0.29	0.30
371	0.51	0.01	0.22	0.13	0.17	0.31	0.29	0.31	0.44	0.31
372	0.47	0.06	0.12	0.01	0.01	0.50	0.36	0.26	0.36	0.38
373	0.13	0.01	0.01	0.00	0.00	0.04	0.01	0.01	0.01	0.01
374	0.40	0.01	0.04	0.01	0.06	0.25	0.18	0.17	0.39	0.25
375	0.25	0.01	0.08	0.05	0.06	0.13	0.07	0.10	0.24	0.20
376	0.52	0.11	0.15	0.07	0.05	0.46	0.44	0.34	0.43	0.40
379	0.15	0.01	0.05	0.01	0.01	0.05	0.03	0.02	0.03	0.03
381	0.47	0.07	0.12	0.18	0.02	0.53	0.55	0.22	0.42	0.49
382	0.39	0.02	0.05	0.03	0.01	0.52	0.35	0.12	0.23	0.25
384	0.34	0.02	0.19	0.08	0.01	0.48	0.30	0.10	0.39	0.32
385	0.37	0.01	0.13	0.12	0.06	0.15	0.12	0.09	0.28	0.34
386	0.26	0.02	0.05	0.01	0.02	0.33	0.19	0.10	0.30	0.23
387	0.36	0.00	0.01	0.08	0.00	0.24	0.14	0.15	0.19	0.1

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Appendix A:

Markov Model Proof

Here I show that there exist a p^* and a p^{**}, where $p^* < p^{**}$, such that the plant stops and chooses f_0 if $p > p^{**}$, stops and chooses f_1 if $p < p^*$, and continues sampling otherwise (see Figure 1 below).

Figure 1

```
          Select f1          Continue Sampling                  Select f0
I-------------------------I-----------------------------------I-------------------------I
0                          p*                                  p**                       1
```

I first suppose that $V(p) = pL$ (i.e., that the firm stops and chooses f_1). I will then show that the p for which this is true is actually an interval. The same argument can then be applied to $\{p: V(p) = (1\text{-}p) L\}$.

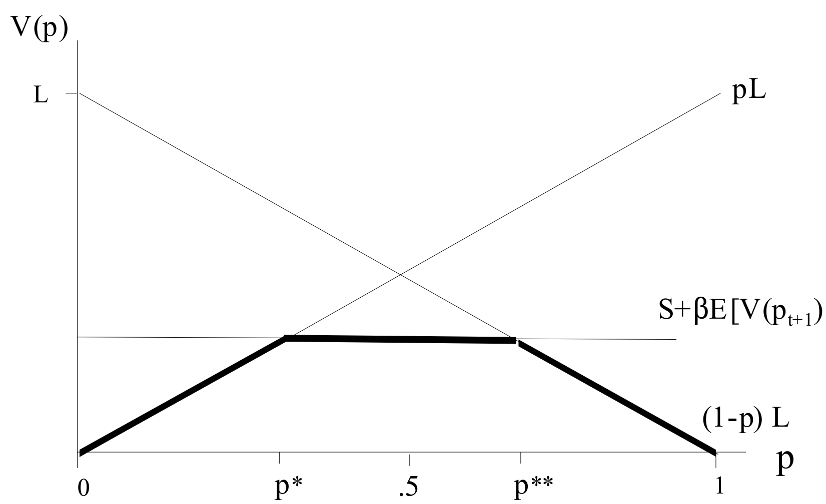
By definition of $V(p)$, it is the case that $V(p)$ can never be greater than pL. That is, $V(p) \leq pL$. However, it can be shown that there exist at least a p for which $V(p)$ is concave in p: observe that at terminal time T, $V(p_T) = min\{ pL , (1\text{-}p)L\}$ is concave in p; that is, there exists at least a p for which $V(p) \geq min\{pL , (1\text{-}p)L\} = pL$. Thus, $V(p)=pL$.

So, $\{p: V(p) = pL\}$ is an interval, which also contains $p = 0$, since $pL = 0$ at p=0. From this it follows that it is optimal to stop and choose f_1 whenever the state p is smaller than some p^*. Similar comments hold for $\{p: V(p) = (1\text{-}p) L\}$.

Figure 2 also shows the optimal policy indicated by the thicker line. Notice that as p approaches 1, $S+\beta E[V(p_{t+1})]$ is greater than $(1\text{-}p)L$ by an amount approaching S. As p

approaches 0, $S+\beta E[V(p_{t+1})]$ is greater than pL by an amount approaching S. Assuming that the continuation set is nonempty implies Figure 2.

Figure 2: Optimal Policy



Appendix B:

Description of Technologies[1]

Computer-Aided Design (CAD)
Use of computers for drawing and designing parts or products for analysis and testing of designed parts and products.

CAD-Controlled Machines
Use of CAD output for controlling machines used to manufacture the part of product.

Digital CAD
Use of digital representation of CAD output for controlling machines used to manufacture the part or product.

Flexible Manufacturing Systems/Cell
Two or more machines with automated material handling capabilities controlled by computers or programmable controllers, capable of single path acceptance of raw materials an delivery of finished product.

Numerically Controlled Machines/Computer Numerically Controlled Machines
NC machines are controlled by numerical commands punched on paper or plastic mylar tape while CNC machines are controlled through an internal computer.

Materials Working Lasers
Laser technology used for welding, cutting, treating, scrubbing and marking.

Pick/Place Robot
A simple robot with 1-3 degrees of freedom, which transfer items from place to place.

Other Robots
A reprogrammable, multifunctioned manipulator designed to move materials, parts, tools or specialized devices through variable programmed motions.

Automatic Storage/Retrieval Systems
Computer-controlled equipment providing for the automatic handling and storage of materials, parts, and finished products.

Automatic Guided Vehicle Systems
Vehicles equipped with automatic guidance devices programmed to follow a path that interfaces with workstations for automated or manual loading of materials, parts, tools or products.

[1]Source: *Current Industrial Reports: Manufacturing Technology 1988, U.S. Bureau of the Census.*

Technical Data Network
Use of local area network (LAN) technology to exchange technical data within design and engineering departments.

Factory Network
Use of LAN technology to exchange information between different points on the factory floor.

Intercompany Computer Network
Intercompany computer network linking plant to subcontractors, suppliers or customers.

Programmable Controllers
A solid state industrial control device that has programmable memory for storage of instructions, which performs functions equivalent to a relay panel or wired solid state logic control system.

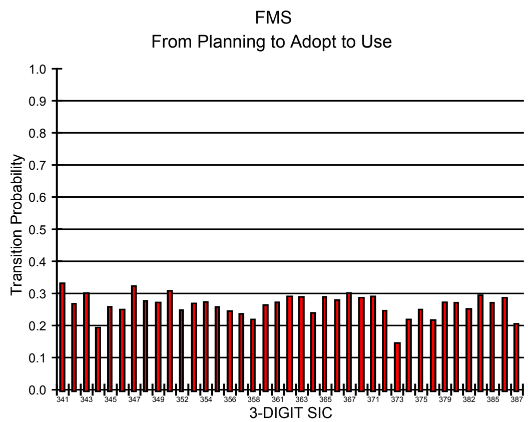
Computers used on Factory Floor
Exclude computers used solely for data acquisitions or monitoring. Include computers that may be dedicated to control, but which are capable of being reprogrammed for other functions.

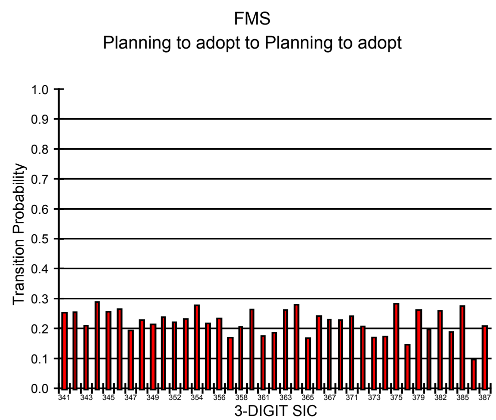
Automated Sensors used on Inputs
Automated equipment used to perform tests and inspections on incoming or in-process materials.

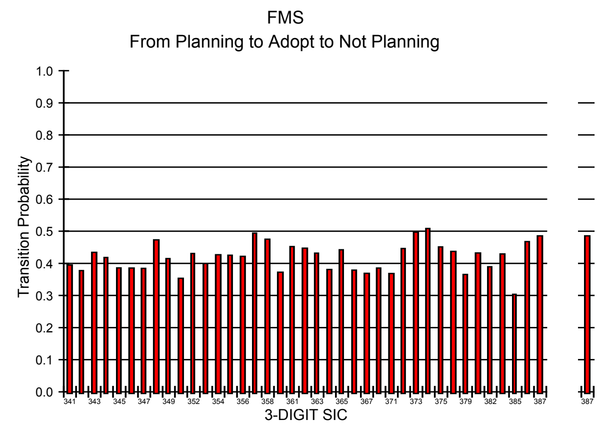
Automated Sensors used on Final Product
Automated equipment used to perform tests and inspections on final products.

Appendix C:

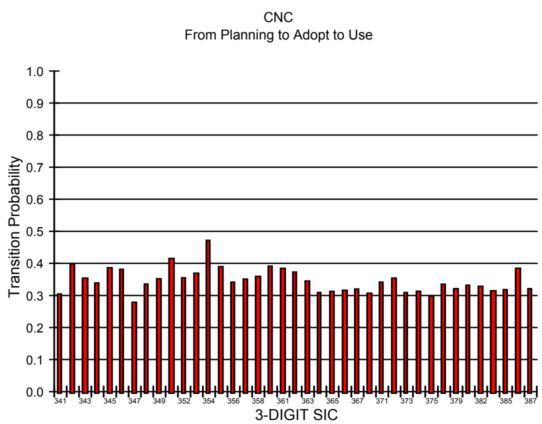
PANEL 1: FMS

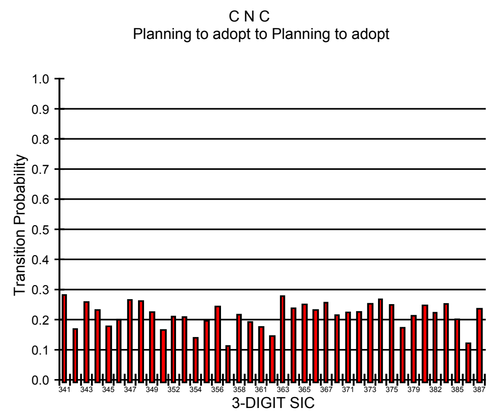


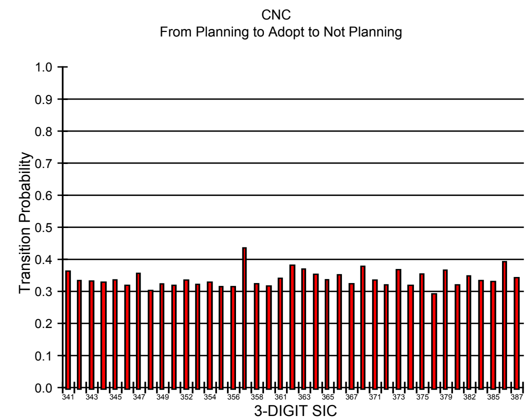




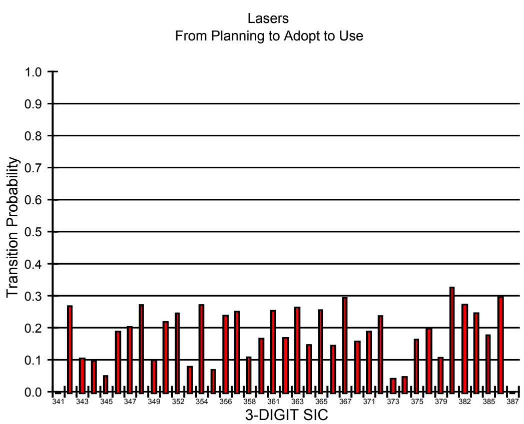
PANEL 2: CNC

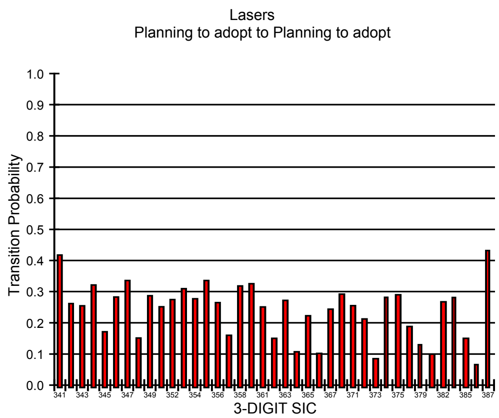

CNC
From Planning to Adopt to Use
Transition Probability
3-DIGIT SIC

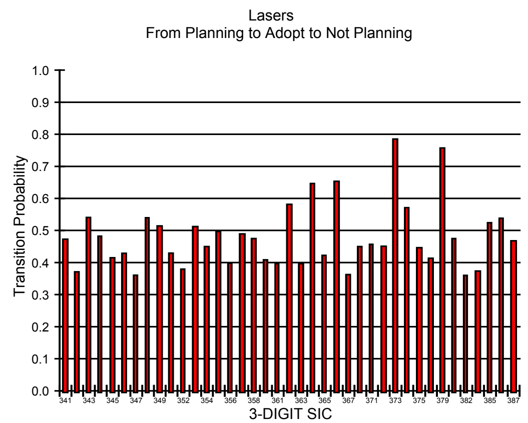

C N C
Planning to adopt to Planning to adopt
Transition Probability
3-DIGIT SIC


CNC
From Planning to Adopt to Not Planning
Transition Probability
3-DIGIT SIC

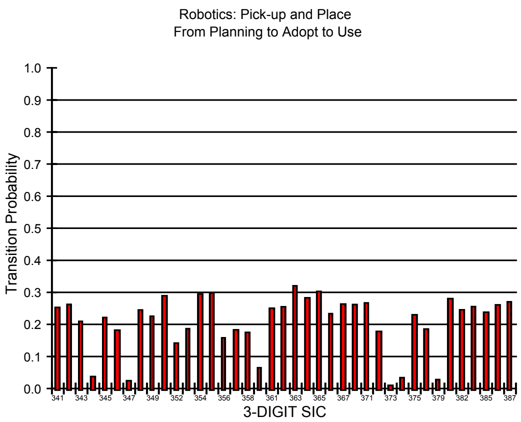
PANEL 3: LASERS

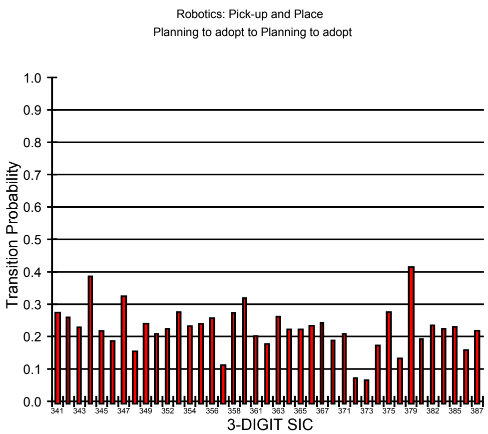


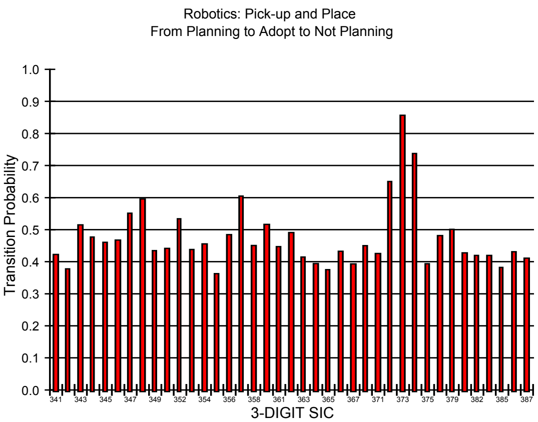




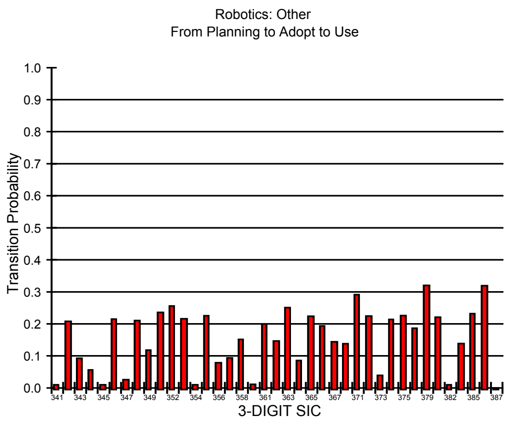
PANEL 4: ROBOTICS, PICK-UP & PLACE

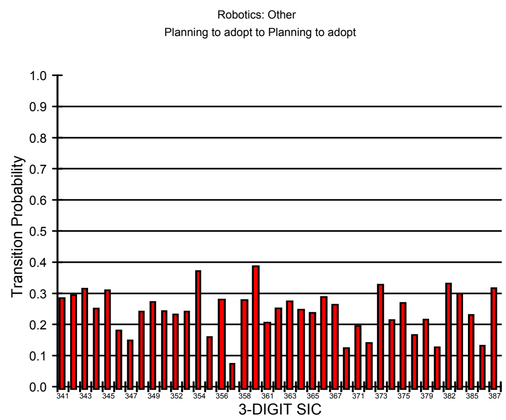


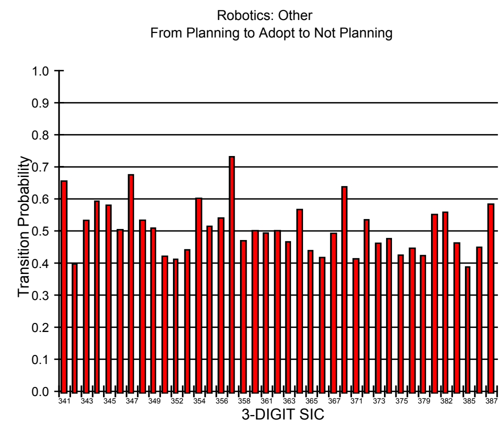




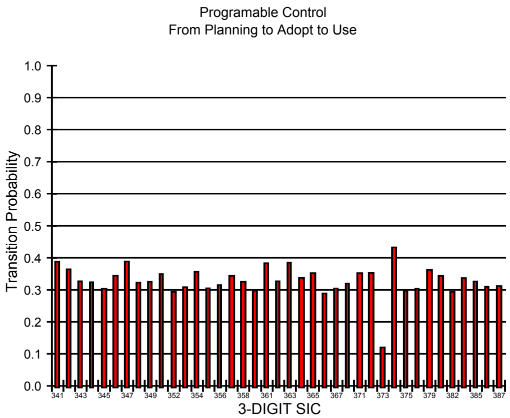
PANEL 5: ROBOTICS, OTHER

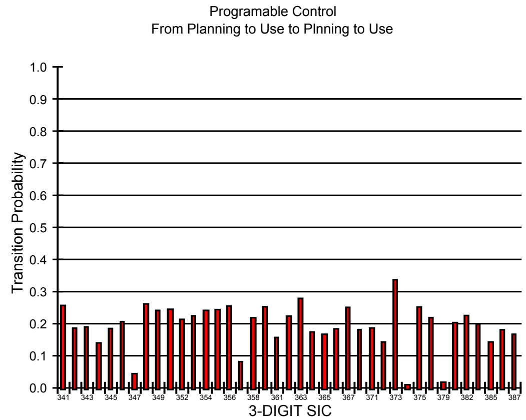


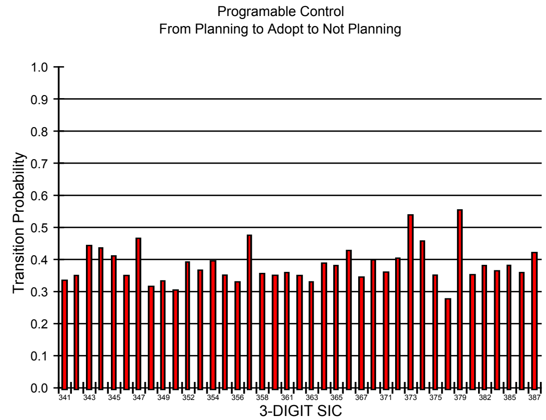




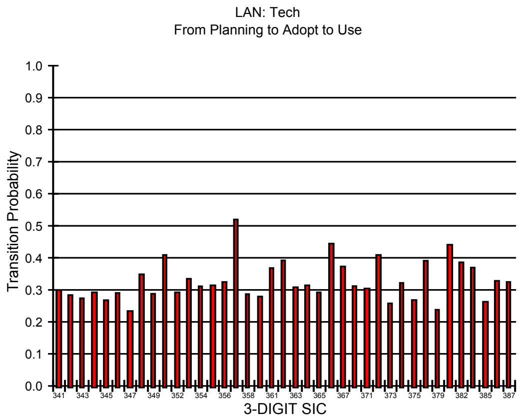
PANEL 6: PROGRAMABLE CONTROLLERS

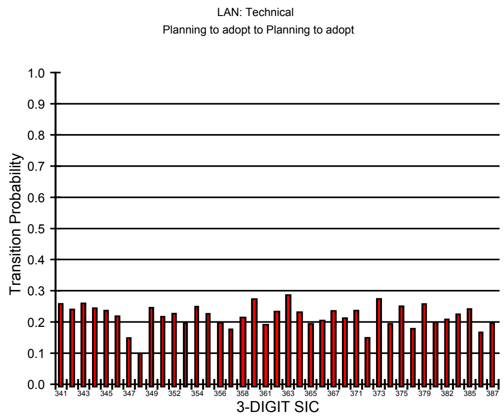


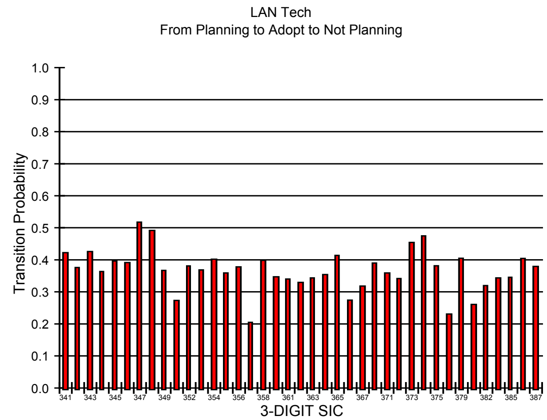




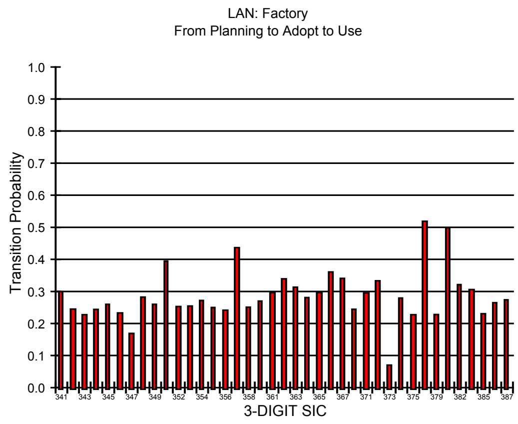
PANEL 7: LAN TECHNOLOGY

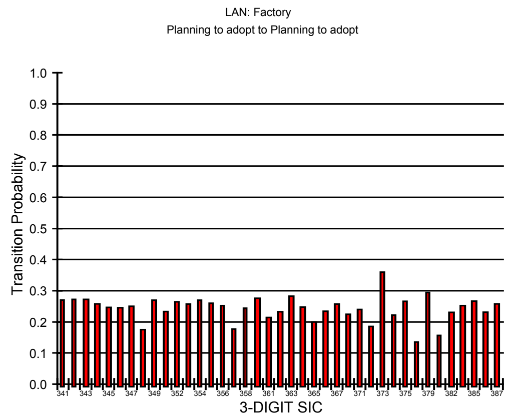


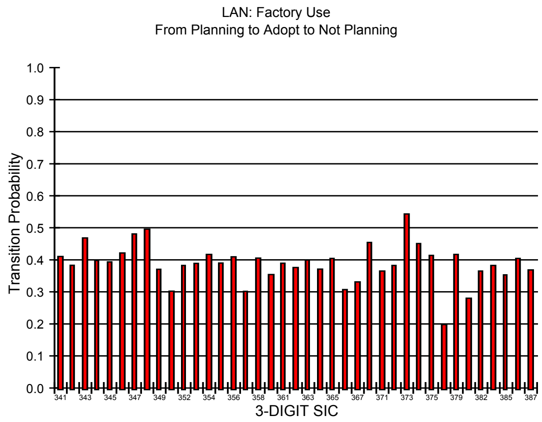




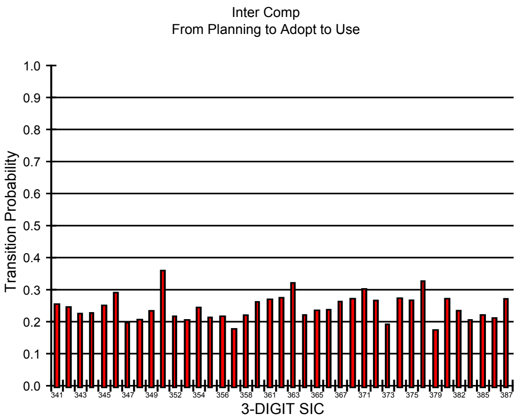
PANEL 8: LAN FACTORY

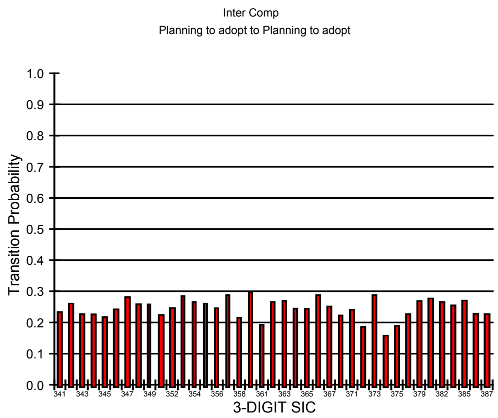


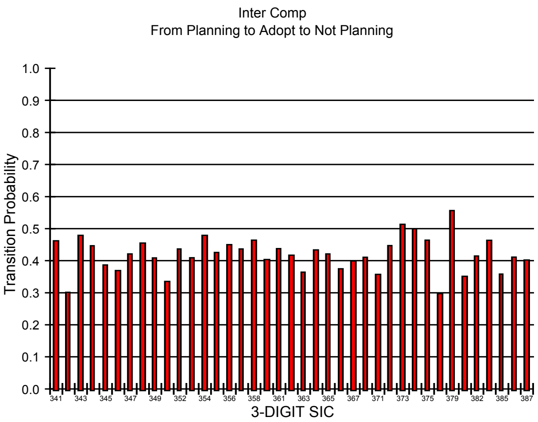




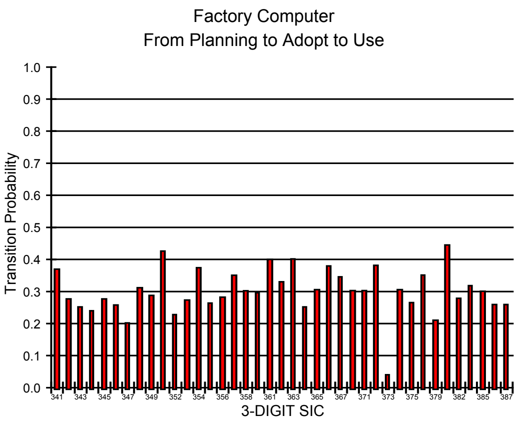
PANEL 9: INTERCOMPANY COMPUTER NETWORKS

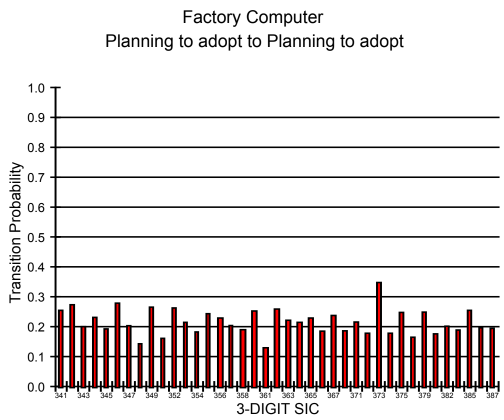


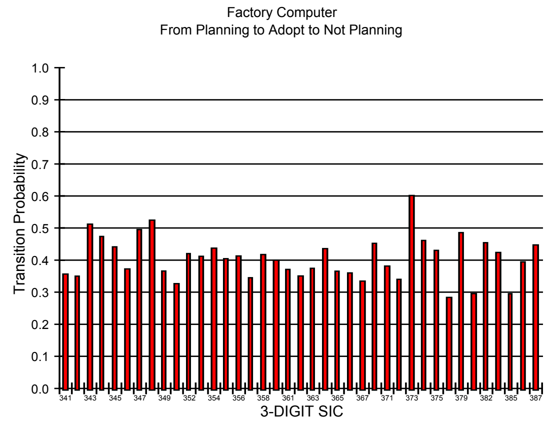




PANEL 10: COMPUTERS USED ON FACTORY FLOOR







ENDNOTES

[1] For example, see Pindyck (1988, 1991, 1993), Dixit (1989, 1992, 1993), Bertola (1987), McDonald & Siegel (1986).

[2] This is why I cannot estimate hazard rates by industry or technology.

[3] See Jaynes (1957, 1984) for development of the basic idea and Lee and Judge (1993) for its application to the transition probability matrix problem.

[4] Given the heterogeneity of technologies and firms, this assumption may be incorrect. That is, the hazard may fall over time, implying that the estimated half-lives are too short. However, my main concern here is to use the estimated half-lives to identify industry and technology outliers. These remain the same whether one uses the transition probabilities directly or the half-lives. I believe that the half-lives are more intuitively pleasing and so present my results in this format.

[5] The DOD deliberately degrades the satellite signal to introduce 100 meters of random error into the civilian signal. With great bureaucratic flair, the Coast Guard then corrects the falsified data and re-transmits it so that ships at sea can, with the proper equipment, accurately fix their position to within 3 meters.

[6] In fact, Ball Corporation's web site features a downloadable diagram of a Flexible Manufacturing System that they use to produce metal cans.

[7] This could be due to the fact that given the 5-year interval between the 1988 and 1993 surveys, and the underlying maximum entropy assumption, the data do not have enough variation to differenciate between the plants that will adopt in five years or in two (since I do not observe the within five year variation).

[8] Recall that the last survey year was 1993 so the clock starts then.

[9] Information obtained at: www.lumonics.com.